Leveraging Digital Twins for Predictive Maintenance: Techniques, Challenges, and Application

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Abstract- *Digital Twin (DT) is a new generation technology adopted in the current complex industrial systems with improved features as a tool to optimise its operations. DTs help generate nearly real-time simulations of an actual entity and facilitate the convergence of physical and digital to enhance existing processes. First introduced by NASA's Apollo program and refined by Michael Grieves, DTs have undergone transformation while adopting modern technological innovations like IoT, big data, and AI. These days, PdM cannot function without them when it comes to planning equipment maintenance to prolong its lifespan and prevent malfunctions. This study provides a comprehensive review of DT applications in PdM after presenting the background, history, and evolution of DT. Information models, data processing modules, data transmission protocols, and the creation and integration of DTs are some of them. Some of the vital approaches for performing predictive maintenance employing DTs include real-time monitoring, the incorporation of AI, simulation and testing benchmarks, and predictive models. The paper also discusses some of the issues involving deployment of DTs such as data management and integration; accuracy; compatibility and constraints of finances. The research aims at enhancing knowledge among scholars and practitioners by demonstrating the state-of-the-art advancement and experience with them. It also describes avenues for future studies to improve the usefulness of DT technology in maintenance predictions.*

Keywords- Digital Twin, Predictive Maintenance, IoT, Big Data, Artificial Intelligence, Real-Time Monitoring.

I. INTRODUCTION

The main parts of a DT are a physical item, an electronic replica of it, and a link that allows one to use virtual analytics to improve the original item's performance [1]. Data and information from both cyberspace and actual space were integrated during NASA's Apollo mission, which gave rise to the idea of the DT. The term "DT," first proposed by Michael Grieves, has now become popular use [2]. Many other models, including mathematical and physical ones, have been used for the systems engineering output by various companies. At the time, NASA described DT as " replicating the whole product life-cycle in virtual space utilising a multi-scale, multi-disciplinary simulation technique that entirely utilises operational history, physical models, sensors, and other data; this provides an exact replica of the real thing." [3][4].

Computer models of physical objects called DT may learn from data collected about their activity and use that information to generate predictions. Manufacturing DT modelling has been made possible by the rise of technologies like the IoT, big data, and edge computing. Significant improvements in process optimisation, downtime reduction, and product quality may be achieved via issue anticipation and preemptive resolution. The US Air Force relied on DT to build stable and dependable equipment, and the technology eventually found its way into other industries looking to streamline product development, testing, and design processes. The workshop's technological infrastructure would be incomplete without intelligent scheduling. Workshop scheduling using traditional algorithmic models, such as Markov models, was neither stable or accurate over the long run when dealing with substantial coupling problems. Production scheduling and planning could be enhanced using DT technology, downtime at the factory floor could be mitigated, and algorithms could be automatically optimised via the utilisation of actual and virtual interactions[5][6].

There is a lack of consensus on the trend, difficulties, and possibilities surrounding predictive maintenance in academics and business despite the fact that it is a significant subject in the DT sector. While DT offers a fresh engineering take on PdM, it is unclear how the new paradigm will affect technical advancements and system performance. Furthermore, no reports of DT advancements for PdM have been made as far as we are aware[7][8]. Consequently, it is important to summarise the most recent advancement in PdM facilitation from DT [3].

A proliferation of sensors, AI, data science, and the IoT has given rise to a new paradigm in engineering called DT. The three main components of DT are the actual object, its digital representation, and the connection. The goal of DT is to improve the physical entity's performance by studying its virtual equivalent. Several researchers claim that DT is important in the engineering sector. Industry 4.0 and smart manufacturing depend heavily on DT. We are presently in the initial stages of DT research. DT's ideas, traits, and framework make up the bulk of the present study. Furthermore, from concept design to logistics, DT is extensively used across the entire life cycle. Particularly, in recent years, publications about DT-driven PdM have become more prevalent and have grown quickly. As DT is a new technology, interest in it is rising, thus it has to be made clear that it is state-of-the-art according to idea, application, and technology[9][10].

By examining and describing its role in predictive maintenance (PdM), this research project seeks to provide a comprehensive understanding of DT technology may enhance a performance, dependability, and efficiency of industrial systems. Through an integration of virtual models with actual data, this research seeks to illustrate the advantages of DT in terms of equipment failure prediction, maintenance schedule optimisation, and overall operational efficiency. In order to offer useful advice for furthering the development of this technology in academic and industrial contexts, the article also examines different techniques and applications. Finally, it highlights issues that are currently encountered while carrying out DT for PdM. The following research contribution is as:

- The paper offers a thorough and current review of digital twin technology, covering its history, development, and present uses in predictive maintenance. This aids in putting DT in the larger framework of modern engineering and production procedures.
- This emphasises digital twins and a variety of methods, including machine learning, real-time monitoring, and scenario testing, may be used to improve predictive maintenance. A strong framework for predicting equipment failures and streamlining maintenance plans is provided by this integration.
- The paper goes into detail on the process of building digital twins, including the data processing modules, communication protocols, and information model. This provides useful information about the specifications and procedures needed to create efficient DT models.
- Integration of data, accuracy of models, and financial limitations are some of the major obstacles highlighted by the research as obstacles to using Digital Twins for predictive maintenance. For DT technologies to be successfully adopted and optimised, several issues must be resolved.
- It covers the many uses of DT at various stages of a product lifespan, including manufacture, servicing, and retirement. This broadens the understanding of how DT can be utilised to enhance performance, reduce costs, and improve decision-making in various contexts.

A. Organised of this paper

The paper starts with an Introduction outlining the research scope. Section II covers overview of digital twin and predictive maintenance. Section III discusses III. techniques in predictive maintenance using digital twins. Section IV explores their applications of digital twins in predictive maintenance, while Section V focuses on challenges in implementing digital twins for predictive maintenance. Section VI provides a literature review, and Section VII concludes with a summary and future research directions.

II. OVERVIEW OF DIGITAL TWIN AND PREDICTIVE MAINTENANCE

In this section, primarily focus on introducing the basic techniques of DT and predictive maintenance, as well as explaining the significance of the research that is being done on the predictive maintenance approach that is based on DT (PdMDT).

A. Digital twin method

Creating and maintaining a digital twin includes every stage of a product's life cycle, including design, production, use, upkeep, and disposal. It also addresses the system or operating environment in which it is integrated. A "digital twin" is a digital replica of an item, resource, method, or idea that is utilised in the manufacturing of products [11]. Data synchronisation reveals the condition of machinery, working circumstances, geometry, and resources; the digital twin is an evolving representation that mirrors actual objects as they change in real time. Typically, there are three components involved in creating a digital twin:

All digital twins typically have the following components: proposed the three components of a DT in his piece, including [12].

- The information model of a physical object.
- A means by which physical objects and digital twins may exchange data.
- A module for processing data that may construct a representation of physical things in real-time from data that comes by a variety of different sources. The proper functioning of the digital twin is dependent on the collaboration of these three components.

Information model: The process of building an information model of a physical thing involves abstracting its features. Models of the physical entity's appearance and mechanism are common components of information models. In the absence of an information model describing the physical entity's properties, data sent into cyberspace becomes meaningless and devoid of context.

Communication mechanism: The most important part of creating a DT is the way the data is sent among the digital and real things. Digital and physical entities rely on two-way real-time data connection to keep their states synchronised in physical space. Through the use of precise information collecting tools (such sensors), a digital twin system is able to obtain and transmit data in real-time while also sensing a condition and performance characteristics of a physical object.

Data processing: The data quality is impacted by the high coupling, non-linearity, and temporal variability of the numerous equipment characteristics in complex systems, as well as by the substantial data redundancy associated with these factors. By storing, screening, processing, and interacting with data in real-time, digital twin technology makes optimal use of data processing technologies like big data to evaluate and analyse changes in the external environment. The next step in realising big data processing and modelling is figuring out how to integrate AI algorithms into big data analysis technologies[13][14].

The following components may also be a part of DT:

- **Platform:** An integrated data management, model management, real-time computing, and data simulation prediction platform is what makes a DT simulation platform useful for software development. A virtual entity may immediately and correctly represent the real entity's status using the digital twin simulation platform. This allows for more efficient system control and timely behaviour guidance.
- **Visualisation:** People may effectively interpret information and make choices by using visualisation technologies. In the digital twin system, the 3D visualisation is more or less an unrealistic view of the system's maintenance and operating condition. Also, it can map out the complicated system's main subsystems virtually, making it easier for staff to see how real items relate to massive amounts of data.

B. Predictive maintenance method

PdM is a preventive technique that uses data analysis and live observation without waiting for the equipment to fail to carry out repairs just before the failure occurs. This technique is always collecting the required operational parameters of a machine-like vibration, temperature or pressure through sensors and IOT devices. The collected data is then pre-processed along with feature selection, and data mining algorithms and statistical methods are then applied for modelling and analysing the failures [15] [16]. It implies that with support of PdM to maintenance management systems organisations can automate the schedule for maintenance and other resources, which can also help to increase overall equipment's life expectancy. Despite the high cost involved in the selection and installation of equipment and personnel training, it has the advantage of lower maintenance costs, better performance and safety in the long run.

III. TECHNIQUES IN PREDICTIVE MAINTENANCE USING DIGITAL TWINS

The following section provides the techniques in PdM based on digital twins.

A. Data-Driven Predictive Models

Predictive models are generated using algorithms derived from modern machine learning and statistics methods to predict equipment failures that require maintenance. Regression models are used for predicting future failures from past data, while classification models categorise the current state of the equipment, whether it is healthy, requires warning or is faulty. Cluster techniques bring together clusters to facilitate the analysis of equipment or operating trends. For information collected from the sensors, time-series analysis, which can come in forms such as LSTM networks, is utilised to determine the first indication of failure [17][18]. These models give solutions where it can be used to identify patterns and behaviours that deviate from regular characteristics and therefore make appropriate maintenance decisions.

B. Simulation and Scenario Testing

Making replicas of physical systems for the purpose of studying their behaviour under various situations is one use of global system emulation and prototyping, which also makes use of major simulation models and scenario testing. As such, these techniques can model various operational conditions and enable one to understand the failure consequences and the suitability of the maintenance strategies. For instance, draw attention to the employ of DT simulations to reviewing maintenance scenarios and schedule arrangements grounded on the conditions of simulated faults [19]. These aspects enable the most efficient maintenance actions and scheduling changes to be determined before application in real practice. In other words, it makes it possible for the different strategies of maintenance to be assessed in terms of their effectiveness across the various scenarios and, as such, the solidity of maintenance planning is guaranteed.

C. AI and Machine Learning Integration

It is because of AI and ML that digital twins are much more capable of doing predictive maintenance. Some of the AI applications are anomaly identification, fault identification, and predictive capability for equipment asset health. For instance, the convolutional neural networks (CNNs) and autoencoders are used to identify irregularities and analysis of faults from the sensors data. When AI is combined with Digital Twins, it's possible to achieve better predictive analysis and estimate the failure with desirable levels of precision [20][21][22][23].

D. Real-Time Monitoring and Alerts

The DT's most important features when used to PdM are real-time monitoring and alarms. Such systems are always monitoring equipment usage and its health state from IoT sensors and other monitoring tools. Alarms are produced when variations from normal working parameters are identified, enabling fast control and upkeep measures. Techniques for real-time monitoring include streaming analytics and edge computing for the processing of data near the source for real-time results [24]. Emphasises the importance of real-time monitoring in reducing downtime and optimising maintenance schedules, highlighting the role of automated alert systems in enhancing the efficiency of predictive maintenance practices.

IV. APPLICATIONS OF DIGITAL TWINS IN PREDICTIVE MAINTENANCE

The following section provides the application in predictive maintenance based on digital twins.

A. Applications in design phase

To decrease a cost of rework and shorten a design cycle, digital twins allow for the merging of information models with physical product models and their iterative optimisation. There are usually four steps to a design process: a) defining the goal, b) developing an idea, c) creating an embodiment, and d) creating the details. [25][26] used a local cobbler as an illustration. The whole lifecycle of the shoes, from conception to final disposal, was handled by a cobbler. This enhanced the availability of information, the traceability of products, and the integrity of data.

Even in this basic "cobbler model," a craftsperson understood the needs of their clients and the limitations of their designs. For each product type and technique, he was also familiar with the specific materials needed. The present tendency towards the complexity and diversity of goods may find a suitable replacement for "the cobbler's mind" in digital twins.

- Iterative optimisation: The goal of any good design, from the initial idea to the final details, should be to meet or exceed the product specification. A digital twin may discover the design's past traces and any upgrades made to them, allowing for iterative optimisation. With an aid of DT, we can optimise the design iteratively among static configuration and dynamic execution, make better material selections for products, and see how dynamic parameters change over time.
- Provide data integrity: The fragmentation of processes that were formerly carried out by a single individual into several parts causes knowledge silos to emerge when product and process knowledge becomes dispersed [25]. Consequently, many stakeholders have access to valuable information that aids in decision-making. Using what is known about the previous generation may help the following generation avoid difficulties that were present in the previous generation [2]. The first proposal for a DT came from the PLM framework. A digital twin is a model that continuously gathers, processes, and stores information on a real location in order to provide enough information for design-phase decisions.
- Virtual evaluation & verification: The goal of every assessment should be to narrow the gap between actual and desired actions. The digital twin approach offers an opportunity to identify and eliminate the Unpredicted Undesirable in addition to focusing most efforts on averting problems and verifying needs, or the Predicted Desirable.

B. Applications in manufacturing phase

The term "manufacturing" has long been associated with the industrial transformation of raw materials into a completed product [27]. The transition from main to smart processes in manufacturing, however, is driven by rising expectations for product quality and the need for quick responses from the market [28]. The closed-loop interplay of physical and digital components is essential in modern production. The core concept of digital twins is the realisation of the interplay and link between the digital and physical realms. Three applications of digital twins were envisaged by Grieves. Together, we can visualise the actual manufacturing processes, ensure that the goods we're producing align with our vision by comparing them to the virtual version, and collaborate to remain up to date on the items we're producing in real time.

- Real-time monitoring: Monitoring processes in manufacturing facilities is not a new concept. On the other hand, digital twins provide an improved method of real-time monitoring. At its core, a DT is a visual data integration tool that works with 3D models. To continue, a digital twin may monitor the present, anticipate the future, and trace history by combining real-time data with expected data and historical data. Investigations into various technologies, including 3D visualisation monitoring, augmented reality, complete elements information perception, etc., are conducted with the aim of implementing DT for real-time monitoring throughout the manufacturing process.

- Production control: It is essential for manufacturing systems to consistently respond to disruptions and carry out predetermined activities. In most cases, the production system is controlled by a centralised execution system that is structured on static assumptions. Through an use of a DT, a physical system may be connected to its virtual counterpart, allowing for comprehensive, real-time, intelligent control.
- Workpiece performance prediction: The production phase is characterised by internal and external problems, such as machine deterioration and raw material fluctuations. Therefore, workpiece performance prediction is both promising and challenging. Predicting the workpiece's performance before actual production begins requires computable virtual abstractions of complicated manufacturing processes together with enough data, which may be provided by digital twins.

C. Applications in service phase

It is common for suppliers and manufacturers to lose control of their goods throughout the servicing phase. The end effect is that their data is hard to manage, access, or achieve a closed-loop DataStream. Even if it may be a faithful depiction of the product's design, the present virtual model is not linked to any particular produced part [29].

- Predictive maintenance: Among the many uses of digital twins; predictive maintenance has reigned supreme from the early days of their creation in both academic circles and business. While many publications do not take into account the impact of the design and manufacturing processes on product performance, present applications are mostly concerned with high-value equipment.
- Fault detection & diagnosis: The data amount is insufficient to train a trustworthy model for data-based fault diagnostics as these physical entities typically function properly most of the time. It does a good job with known anomalies in physics-based fault diagnostics but doesn't know what to do with unknown abnormalities. With a digital twin, you get the best of both worlds: a product's data and a multi-physics model that works together.
- State monitoring: A digital twin can do more than just keep an eye on data discrepancies compared to expectations; it may also provide alternative interpretations of the data. The mechanism of failure may be better understood by comparing the simulated data from the DT with the collected data. Compared to conventional state monitoring, digital twins use less data to recreate the physical object's present state in a virtual environment since they give an accurate model that is updated throughout the product lifespan.

D. Applications in retire phase

The retirement period is sometimes disregarded as a distinct stage. It is common for information on the behaviour of a system or product to be lost when it is retired. When one generation of a system or product learns from another, it usually fixes the same issues that plagued the previous generation [2]. During the retire phase, it is cost-effective to preserve the digital twin in virtual space as it holds all the information about the physical twin's lifetime.

V. CHALLENGES IN IMPLEMENTING DIGITAL TWINS FOR PREDICTIVE MAINTENANCE

Several obstacles must be overcome before Digital Twins (DTs) may be used for predictive maintenance to their full potential. These challenges span technical, organisational, and practical domains.

A. Data Integration and Management

Ensuring high-quality and consistent data is crucial for accurate predictive maintenance. Integrating diverse data sources and addressing security and privacy concerns can be challenging.

- Data Quality and Consistency: Reliable predictions depend on high-quality, consistent data. Inaccurate or noisy data can undermine model effectiveness [30].
- Data Security and Privacy: Security and privacy are the biggest concerns because operational data is sensitive in nature [28].

B. Model Accuracy and Complexity

Realistic replication of the systems is only possible when the Digital Twin models are well-calibrated and validated to a great extent. Hence, understanding how to control model complexity while seeking high performance is a critical issue.

- Model Accuracy: Physical systems must be modelled correctly. Thus, such methods as refined calibration procedures are required in order to enhance the accuracy of models.
- Calibration and Validation: On their calibration and validation, one should be quite attentive to preserve models' efficiency. That is doing modulations and checking models conformities to real-world conditions [31].

1) Integration with Existing Systems

An integration of DT with legacy systems is not always easy because of compatibility issues. Quoting solutions for large systems requires large computations hence it is a time-consuming process.

- Legacy Systems Compatibility: There are always difficulties in incorporating DTs into more traditional infrastructures. Specific interfaces and middleware solutions are normally needed.
- Scalability: Information technology chiefs should be aware that embedding DTs with other related architectures can be difficult. Service middle-ware solutions and custom interfaces may be necessary.

C. Cost and Resource Constraints

Often, Digital Twins are introduced with high investment costs, and hence, proper resource management is critical for deployment. Outsourcing Comprehensiveness of control strategies for cost and resource usage is inevitable.

- High Implementation Costs: There are also costs associated with implementing such as high initial investment to procure the necessary technology, and qualified people.
- Resource Allocation: Implementation also needs resources hence an efficient management of resources in order to meet the set goals.

D. Human and Organizational Factors

Digital Twins need specific competencies to be properly executed and change management plans to minimise the resistance of the organisation. Countering these challenges will require capacity building and engagement of the various stakeholders.

- Skill Gaps and Training: Implementation of DT requires specialist skills. Training programmes remain critical in an organisation so that skills can be gotten back on track.
- Adoption Resistance: There is a possibility of organisational resistance when implementing new technologies. These barriers can be addressed using strategies to prove value and engage stakeholders.

VI. LITERATURE REVIEW

All the prior research that has been carried out in this field has primarily used statistical techniques after overcome a challenge associated with an use of DT in a context of predictive maintenance.

In this paper, Adeyemo, Bahsoon and Tino, (2022) provide a new approach to predictive fault modelling that may aid software analysts and CPS testers in their testing strategies by using surrogate-based digital twins to investigate potential defects. This method foregoes the CPS in favour of a RNN surrogate model with LSTM for prediction purposes. Water distribution and air pollution monitoring systems are two CPSs that we evaluated using our surrogate-based DT predictive modelling methodology. Our method did adequately in forecasting numerous time steps, according to the data[32].

In this paper, Xue et al., (2023) offers to improve the efficacy, efficiency, and accuracy of substation inspection and maintenance procedures by making use of digital twin technology's simulation capabilities, powerful analytics, and real-time data. The outcomes have shown that the system applied through digital twins is superior to the other methods in comparison by the aspects of efficiency, accuracy, cost-effectiveness, and less time-consuming maintenance. The deficiencies of the old methodologies are highlighted in contrast to the digital twin-based system's benefits when discussing the concept's application. This paper demonstrates the value that digital twin technology can bring to enhancing substation efficacy and reliability and assist with enhancing substation assessment and upkeep[33].

This paper, Ersan, Irmak and Colak, (2024) address the nine elements of smartness with regard to their dual nature, functionality, flexibility, and optimisation of resources. Using a smart city example, the paper illustrates how digital twins facilitate proactive interventions, resource optimisation, and informed decision-making in domains like traffic management, energy optimisation, and public safety. It highlights a significance of DT in fostering collaboration, innovation, and resilience, empowering cities to address complex challenges and create inclusive, sustainable environments. In conclusion, digital twins emerge as indispensable tools in realising the vision of smart, connected, and adaptive cities, poised to navigate the complexities of the contemporary urban landscape and pave the way for a sustainable future[34].

This paper, Casillo et al., (2022) uses a sensor network and DL algorithms to analyse sensor data, introducing a revolutionary way to preserving buildings using HBIM. The presentation will concentrate on a case study with the Archaeological Park of Pompeii and how they use a web-cloud-IoT platform to manage and distribute data acquired in real time. After that, the data is run through a GAN to foresee potential problems with Cultural Heritage Buildings, namely with the indoor humidity that is so important for preserving ancient buildings[35].

This study, Timjerdine, Taibi and Moubachir, (2024) provides crucial insights for researchers, practitioners, and industry professionals by classifying technologies based on their maturity levels and exploring their applications. It underscores the necessity for continuous exploration and implementation of emerging technologies in aircraft maintenance, emphasising collaboration between stakeholders to realise the full potential of Industry 4.0. Ultimately, this research aims to pave the way for innovative, efficient, and technologically advanced practices in aircraft maintenance, promising a future where maintenance processes are safer, cost-effective, and more sustainable[36].

This study, Oviedo et al., (2024) uses the dc-ac inverter thermal model in a PV system that is linked to the ac grid to painstakingly extract data on load, input power, and temperature as inputs and demands change. After that, a full analysis may be conducted by combining the findings of this simulation with a dataset of all relevant signals spanning a whole year. You may use this dataset to train an ANN that can accurately predict, during a heat cycle, the lifespan consumption or damage up to a maximum of 78.90%[37].

This paper, H. Chen et al. (2023) propose a DT-based stability architecture for robotic drilling systems. The overall virtual entity model of the system is studied by mathematical and physical method, and the virtual entity and physical entity of the system operates simultaneously by combining the virtual and physical mapping of the system. The experimental results demonstrate that the twin model exhibits a high level of accuracy in robot drilling. It has the flexibility to watch parameters in the course of the machining process and store data in the process. By using mathematical models for prediction and optimisation in the tasks' solution, it strengthens system stability in its way[38].

This paper, Han et al., (2023) offers a concept of IoV Information Management System (IIMS) that incorporates blockchain and parallel intelligence to solve these problems. As a result, the problems that occur due to the single point of failure in centralised server systems, integrated to the suggested method makes use of blockchain distributed nature and data redundancy. Sharing data is safe, secure, and uncompromised thanks to blockchain's anonymity, immutability, and traceability. Furthermore, blockchain-based solutions, such as incentive systems and decentralised autonomous organisations (DAOs), encourage cars to share data while guaranteeing the data's quality[39].

Table. 1 Presents a comparative table for leveraging digital twin for Predictive Maintenance

Ref	Methodology	Key terms	Limitations & future work
[32]	LSTM-based surrogate model for predictive fault modelling in CPS, supporting both direct and iterative forecasting.	Water distribution system, air pollution detection system	Future work may include enhancing model accuracy and applying the framework to other CPSs or different domains to generalise the approach.
[33]	An evaluation of a DT-based system for the inspection and maintenance of substations was conducted using five case studies.	Substation inspection and maintenance data	Future work could focus on further enhancing real-time data processing, exploring additional case studies, and expanding the application to other types of infrastructure.
[34]	Digital twins in smart cities for predictive maintenance, performance optimisation, and data-driven decision-making across domains like traffic management and energy optimisation.	Smart city data across multiple domains	The need for strong data security measures and the difficulty of integrating various data sources are limitations. Future work could explore further applications in other domains.
[35]	HBIM integrated with sensor networks and deep learning (GAN) for cultural heritage preservation, focused on analysing humidity issues.	Data from Archeological Park of Pompeii	Future work may involve expanding to other heritage sites, improving the GAN model, and incorporating additional environmental factors for comprehensive building preservation.

[36]	Classification of emerging technologies in aircraft maintenance, with a focus on collaboration and implementation of Industry 4.0 technologies.	N/A (conceptual framework with industry examples)	Future work could explore the practical implementation of these technologies and their impact on maintenance processes in various aircraft models and environments.
[37]	Thermal modelling and Monte Carlo simulation for PV system inverter lifespan prediction, with Weibull distribution analysis.	Year-long dataset of thermal, input power, and load data from a PV system	Limitations include the accuracy of predictions and the complexity of real-time applications. Future work could improve prediction accuracy and extend the model to other system components.
[38]	Digital twin-based stability architecture for robotic drilling systems, with real-time monitoring and optimisation through mathematical models.	Robotic drilling system data	Future work might include expanding the model to different robotic systems, improving real-time response, and integrating with other digital twin platforms for broader applications.
[39]	IoV Information Management System leveraging blockchain and parallel intelligence for secure data sharing, incorporating DAO for collaborative analysis.	IoV data from blockchain networks	Limitations include potential scalability challenges and the need for more robust incentive mechanisms. Future work could address these issues and explore integration with other IoV systems.

A. Research gaps

Despite the general limitations that can be noted concerning the articles included in this collection, the authors manage to illustrate the possibilities of applying digital twin technology in different fields. In all these studies, DT holds the capability to enhance various procedures, including the identification of problems, prognosis of system faults, and maintaining stability in the system without comprehensive verification and simple up-scaling tests inside real-world fields. Instead, the usage of case studies and imitative situations, as valuable as they might be, do not cover all the challenges and the essence of applying these technologies on a large scale in different conditions. Besides, it can be stated that, in many cases, the studies focus on the technological aspect of the solutions discussed, paying little attention to the organisational or socioeconomic factors that may hinder or facilitate the implementation of the technology in question. Thus, there can be no doubt that digital twins are capable of delivering radical changes in businesses; however, far more systemic, integrative, and conceptually rigorous research is needed to support the diffusion of digital twins.

VII. CONCLUSION AND FUTURE WORK

Predictive maintenance is becoming more crucial due to the industrial industry's upgrading and growth; nevertheless, conventional predictive maintenance methods often fall short of meeting these demands. Research on digital twin-based predictive maintenance has recently exploded in an industrial sector. Overall, it can be described that DT technology marks a new epoch of the PdM, by providing a higher level of development for industrial systems. By making digital replicas of physical assets, DTs facilitate real-time sensing, modelling and analysis to support decision-making, which assists organisations in predicting conventional equipment breakdowns and, in turn, scheduling the optimum time of equipment maintenance. Finally, this study provided an overview of DT concepts and methods, as well as DT components and integration methodologies. It has also identified the applications of DTs at each step of a product lifecycle, including design, manufacturing, servicing, and end-of-life. However, the DT's for PdM has the following limitations; data management/ integration, model accuracy, compatibility with existing frameworks and systems, cost factors, and stakeholders. This paper presents details of these challenges that are crucial to the successful implementation and enhancement of DT technology in industries.

To further improve prediction efficiency, future research should focus on refining DT's algorithms and ML approaches. Thus, further investigations should be made in order to enhance the interface of DTs with other traditional processes that are still employed in different industries and scenes, which is needed to overcome compatibility and scalability issues. Related to this, attempts should also be made to minimise the implementation costs of DT, which could perhaps be done through innovation in technologies and efficient procedures. Also, the employment of DTs expands, there is a significance need to determine general frameworks and protocols for the usages of DTs deployment and running. Last of all, a combined effort from engineers, data scientists, and industry specialists will help to limit the current issues and adapt DT technology for a purpose of prescriptive maintenance.

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